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Review of environmental efficiency and its influencing factors in China: 1998–2009

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ABSTRACT

Improving environmental efficiency has been regarded as an objective requirement and an inevitable path to build a resource-saving and environment-friendly society in China. The slacks-based measurement (SBM) model with undesirable output is applied to measure the environmental efficiency of provinces in China from 1998 to 2009. Then, by the Tobit model, we can empirically test the impact of influencing factors on the environmental efficiency. It demonstrates the low value of the environmental efficiency of each province with an essentially descending trend on the whole and the distinct differences between the environmental efficiency of those provinces. Besides, GDP per capita dependent on foreign capital and trade, environmental awareness and population density have obviously positive impacts on environmental efficiency. And the proportion of the secondary industry in the GDP shows a significantly negative impact on the environmental efficiency.

Contents

1. Introduction

In spite of its booming economy of high speed and striking achievements, China has been confronted with environmental problems since the reformation and opening-up. China has evidently been stricken with a host of serious problems, including

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the low efficiency of resource utilization and the declining environmental quality. According to the rankings of the world Environmental Performance Index (EPI) in 2010, China got 49 points which ranked the 121st among 163 countries (See "Iceland Leads Environmental Index as U.S. Falls," http://epi.yale.edu/Home), which means that the environmental improvement in China is an urgent task. At present, the administration of the laws and regulations on environmental illegal act is proved to be more and more rigorous under stricter pollutant emission standards on environmental protection. Consequently, with the economic development, China has to improve and optimize environmental efficiency, which is considered to be the objective requirement and the inevitable path to build a resource-saving and environment-friendly society. And it is undoubtedly of theoretical value and practical significance to measure and calculate the environmental efficiency of each province in China and then make the empirical analysis of the results.

The rest is organized as follows. The second section is literature review. In Section 3, we show the influencing factors, index selection and data sources of environmental efficiency, then apply the DEA model to measure the environmental efficiency in China. The empirical analysis of influencing factors is taken in the fifth section. Finally, the structure analysis and policy proposals are given.

2. Literature review

Data envelopment analysis (DEA), i.e., one of the main tools to analyze the efficiency of the production process, has attracted many researchers when it was proposed in 1978 [1]. It has made a great of extensions by the researchers. The analysis of the efficiency on the production process in the study of environmental issues primarily arose in the 1980s. Along with more attention from the international community on environmental sustainability issues, some efficiency analysis models, especially the non-parametric estimation method DEA, have been widely applied in the study of environmental efficiency [2]. So far, the researchers have made a great number of achievements on the environmental efficiency evaluation and management by the DEA efficiency models [3,4].

Early research was designed to process undesirable outputs as the shadow prices. Färe et al. firstly proposed a nonlinear programming method and processed pollution variables by virtue of the input–output's nature of receipt for weak processing, which was grounded on the thought that sacrificing good outputs can achieve the goal to reduce undesirable outputs like pollution [5]. Since in the environmental efficiency evaluation, undesirable outputs like pollutants are expected to be as small as possible, it can be considered as a feasible method to add pollutants, like input indicators, into the DEA model to analyze the environmental efficiency of decision-making units. For instance, a production frontier on the basis of DEA's environmental protection was proposed to explore and analyze the environmental efficiency [6].

Data conversion function transforms the undesirable outputs that has the smallest possibility into the desirable outputs as large as possible with the pollutants that are still counted as sorts of outputs, then processes the transformed outputs as kinds of ordinary outputs and applies the traditional DEA model to the analysis of the environmental efficiency in decision-making units. Golany and Roll gave a method of nonlinear data conversion through a conversion function to transform pollutants into a form of desirable outputs as large as possible, but this method cannot meet the requirements of the model's convexity [7]. Scheel and Zhu also proposed a method, which converts the value of undesirable output into its reciprocal, and subsequently treat the reciprocal as a desirable output [8,9]. Seiford and Zhu suggested that all negative undesirable outputs can be converted into the positive forms, which can be attained by multiplying these undesirable outputs by -1 and the method can measure the environmental efficiency in the thought of undesirable outputs [10]. Based on the classification–invariance of the BCC model, Jahanshahloo et al. continued to develop this method and found that although this method could effectively maintain the linear and convex relationship, it is against the actual production process [11]. So the CCR model would not be able to maintain the classification–invariance, and this method of efficiency evaluation might be biased.

According to the distance function method, Chung et al., based on the pollutants' nature of receipt for weak processing, raised a data envelopment environmental analysis model when they thought of pollutants put in the frame of technical efficiency analysis [12]. The model gives a specific direction, making the undesirable outputs decrease in the same proportion as the desirable outputs increase, so this method breaks through the customary efficiency evaluation method and shows its superiority in some degree. Tone built the slacks-based measurement (SBM) model on the basis of slackness measurement, which takes into account the slackness problems of inputs and outputs caused by the radial and angular choices [13,14]. Dyckhoff and Allen put forward a new evaluation method of environmental efficiency in line with the additive DEA model, which pays more attention to the undesirable output and undesirable input indicators simultaneously [15]. Jahanshahloo et al. used that model to evaluate the environmental efficiency of the decision-making units [11]. In addition, other researchers developed a couple of environmental efficiency models to consider the undesirable outputs, which can be applied in the evaluation and analysis of environmental system, such as the assessment for the impacts of the environmental regulation, the evaluation for the environmental performance, the estimation of pollutants' shadow prices and the quota system of pollutant emission [16–18].

The above researches on undesirable outputs mainly focused on the technical aspects of non-parametric DEA, but lacked the systematic studies of the environmental efficiency, which only aimed at the latest actual situations (particularly the practical problems of the developing countries such as China). Most of the existing models do not consider the impacts of the uncontrollable external factors on the efficiency analysis, and the regression analysis of the evaluation results is rare in these models. Furthermore, these models neglect the study on the statistical properties of the models themselves in consideration of undesirable outputs and statistical tests with the analysis of the problems of China's environmental efficiency.

3. Influencing factors, index selection and data sources

Based on the review of related works in the previous researches, we take into account the economic developmental level, the degree of opening-up, the environmental protection and regional factors.

3.1. Economic developmental level

Most of the works adopted the average GDP, which can accurately reflect and depict the disparity of the economic development level in different regions, as the best index to measure the economic development level. The environmental Kuznets curve concerning environmental preference theory maintains that there will be a higher requirement for environmental quality than for income and employment with the continuous improvement of people's living standard, which leads to people's inclination of promoting environmental quality and efficiency. Thus in this paper, the average GDP is selected to reflect the

economic development level. The average GDP, accounted by the current price based on that in the year 1952, is transformed with logarithmic method in empirical study to keep consistent with the content described previously. The second part in consideration is the industrial structure. China has long been proceeding on the way of traditional industrialization. More resources will be exploited in the progress of the elevation of the status of industry in the national economy, that is, water carrying capacity and the rate of resource regeneration cannot keep up with the rate of resource consumption. This phenomenon will result in a series of problems such as more serious pollution and lower environmental efficiency. Furthermore, the proportion of the industrial production value to the GDP, which is closely correlated with the environment, is applied as an index to evaluate the industrial structure. The data in this paper are acquired by China Statistical Yearbook and Statistics Compilation in 60 Years of New China in previous years.

3.2. The degree of opening-up

The degree of a country's opening-up can be embodied in various aspects, like import and export of technology, labor transnational mobility and internationalization of capital and trade. According to the pollution haven hypothesis, a country which is likely to enact less stringent environmental regulations on pollution-intensive production, has a comparative advantage in a polluted good and this will bring about more and more polluting industry. Because of the close correlation of the degree of environmental regulation and the average GDP in a country, these developing countries will become the pollution haven and a wealth of foreign capital in direct investment which will flow into those pollution-intensive industries in these countries.

On the contrary, some other researchers insist that the degree of direct foreign investment is mainly decided by the integrity degree of the host law, political stability and economic development level. However, the environmental regulations have nothing to do with the location choice of Foreign Direct Investment (FDI). Moreover, the factor endowment hypothesis argues that scarce capital countries target their development on labor intensive industries when abundant capital countries concentrate their attention on developing capital intensive industries. Thus, the degree of opening-up has an inconclusive effect on a country's ecological efficiency.

According to the availability of data, this paper selects the actually utilized Foreign Direct Investment and the proportion of the foreign trade amount to the GDP to reflect the degree of each province's opening-up degree in China. Note that the data from 1998 to 2008 are originated from Statistics Compilation in 60 Years of New China, and that in 2009 is taken from China Statistical Yearbook in the edition of 2010. When considering that the units of FDI and trade figures are both ten thousand dollars, all the data are converted to China's currency in reference with the exchange rate in the statistical yearbook.

3.3. Environmental protection

While environmental protection contributes much to the improvement of environmental efficiency, it is largely characterized by non-excludability and non-competitiveness. Thus, it is urgent for the government to strengthen the administration. The government plays a significant role in reducing the environmental pollutant emission. Blindness and irrationality on the way of market-oriented economic development might result in some environmental problems. To realize the aim of improving the environmental efficiency, the government should emphasize the significance of fulfilling the responsibility of administration and integrating economic, and realize the red ministration and juristic mean to regulate the market behaviors. Strengthening the consciousness of the populace is essential to the environmental protection. Therefore, the government should start from the mass media and education, then put more attention to the propaganda on the group of teenagers and students, augment the investment on environmental protection facilities enacting concrete rules and regulations, and put the environmental protection into agenda are also inevitable. All of those will render the environmental protection a new department with self-development and self-reliance. Furthermore, from their own viewpoints, those enterprises should pay more attention to the pollution control, augment the investment on pollution regulation, and increase the strength of environmental protection.

In the aspect of environmental protection, this paper investigates the environmental consciousness and the strength of environmental protection. Herein, the former one can be replaced by the level of education. The proportion of the population with an education level is above high school in each province is used to represent this. The latter one can be expressed by the proportion of the investment on industrial pollution regulation to the GDP. The datum is taken from China Education Statistical Yearbook and China Statistical Yearbook in previous years.

3.4. Regional factors

The differences in geographical locations of distinct provinces might arouse the disparity of abilities in acquiring technology, information, time and intermediate factors and dissimilate the market competition consciousness in each province, which further affects their environmental efficiency. Except the different geographical locations, regional factors including population, resources, climate and some other hardware conditions can be a "two-edged sword", which will make it difficult to determine their impacts on the environmental efficiency.

Table 1
Illustration of indexes.

Indexes	Explanatory variable	Abbreviation	Units	Meaning
Economic developmental level	Average GDP	*GP*	RMB yuan/person	The proportion of the GDP to the local population
	Industrial structure	*ISG*	%	The proportion of the industrial production value to the local GDP
Degree of opening-up	Dependence of Foreign Capital	*FG*	%	The proportion of the actual FDI to the GDP
	Dependence of trade	*TG*	%	The proportion of the total amount of foreign trade to the GDP
Environmental protection	Strength of environmental protection	*CG*	%	The proportion of the investment on industrial pollution regulation to the GDP
	Environmental awareness	*EA*	%	The proportion of the population with an education level above high school
Regional factors	Population density	*PD*	People/km^2	The proportion of the total population to the regional area by the end of the year

In order to normalize the data, regional factors can be expressed by the population density and converted into the logarithmic form in empirical study. Herein the population is derived from the permanent resident population in China Statistical Yearbook in previous years, and the size of regions is taken form the central government portal website. The illustration of the variables above is listed in Table 1.

4. Establishment of the model

4.1. The theoretical model

At first, the censored regression model is introduced to study the regression problem in cases where in observation of a certain individual some variable indexes in data sets are censored. Censoring a variable does not mean deleting some data, and the essence is processing regression models with censored data in proper means.

As a typical representative of censored regression model, the Tobit model is brought forward when James Tobit sought for a model, which the dependent variable is a fragment value to study the people's demand on consumer durable goods. If the dependent variable is a fragment value, the method of OLS parameter estimation might cause huge bias and inconsistence. The method of maximum likelihood estimation (MLE) can avoid some problems in the OLS estimation. Furthermore, the Tobit regression model, of which the values of explanatory variables are limited and the dependent variables are expressed by the actual value, can also be nominated as the truncated regression model.

Assume the errors observe the distribution of $N(0,\sigma^2)$. Thus we can obtain the Tobit model:

$$Y_i^* = X_i{}'\alpha + \delta\varepsilon_i$$
$$Y_i = \begin{cases} 0, & \text{when} \quad Y_i^* \le 0 \\ Y_i^*, & \text{when} \quad Y_i^* \ge 0 \end{cases}$$
$$\varepsilon_i \sim N(0,\sigma^2) \tag{1}$$

where $X_i{}'$ is the explanatory variable, Y_i^* is the latent variable, and α is the correlation coefficient; δ, a scaling parameter which is introduced to obtain the likelihood function and estimated along with the parameter α, is actually the standard deviation of residuals in normal models. When $Y_i^* \le 0$, we observe $Y_i = 0$ and define it as the 'limited' observed value. When $Y_i^* \ge 0$, $Y_i = Y_i^*$ is defined as 'unlimited' observed value. From the model (1), it is supposed that the 'limited' observed values are all given 0, when these 'unlimited' observed values are assigned with their actual values.

4.2. Measurement of environmental efficiency

Slacks-based measure (SBM) as a remarkable approach for solving the problem was first proposed by Tone (2001). Different from CCR, BCC and some traditional measures which assume the proportional reduction (enlargement) of input (output) vectors, SBM model is non-radial and deals directly with input excess and output shortfall. This measure is invariant to the units of measurement and is monotone increasing in each input and output slack. Thus, we choose SBM model to measure the efficiency. Based on the SBM model, which is non-radical and non-angular, we select labor force, capital stock and energy consumption as the input indexes, and we adopt GDP, waste gas emission, wastewater discharge and solid waste emission as the output indexes to separately measure and calculate the environmental efficiency of each province in China. The obtained numerical values are presented in Table 2.

The overall value of environmental efficiency of provinces in China remains at a low level and the majority of these values show the declining trend. The provinces with the highest value consist of Beijing, Tianjin, Shanghai, Liaoning and Yunnan, and they are retained on the frontier and act as "the best practitioner" to construct environment-friendly cities. Therefore, they can be

Table 2
The values of environmental efficiency of China from 1998 to 2009.

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Anhui	0.30	0.29	0.30	0.29	0.27	0.28	0.27	0.26	0.27	0.25	0.26	0.25
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Fujian	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.57	0.67	0.72
Gansu	0.32	0.32	0.31	0.31	0.29	0.27	0.26	0.25	0.24	0.23	0.24	0.24
Guangdong	0.46	0.42	0.40	0.39	0.37	0.36	0.34	0.34	0.35	0.33	0.32	0.31
Guangxi	0.38	0.38	0.38	0.35	0.34	0.31	0.28	0.30	0.31	0.29	0.30	0.28
Guizhou	0.13	0.13	0.13	0.13	0.13	0.11	0.11	0.12	0.12	0.12	0.13	0.13
Hebei	0.49	0.46	0.44	0.43	0.41	0.39	0.35	0.36	0.36	0.34	0.33	0.32
Henan	0.32	0.33	0.32	0.31	0.30	0.28	0.26	0.25	0.24	0.22	0.21	0.20
Heilongjiang	0.34	0.34	0.38	0.39	0.37	0.39	0.38	0.41	0.41	0.39	0.38	0.34
Hubei	0.36	0.37	0.37	0.38	0.36	0.35	0.31	0.33	0.33	0.32	0.32	0.32
Hunan	0.33	0.39	0.42	0.42	0.39	0.33	0.29	0.33	0.34	0.31	0.31	0.30
Jilin	0.48	0.45	0.47	0.49	0.47	0.45	0.42	0.39	0.36	0.31	0.29	0.28
Jiangsu	0.56	0.54	0.52	0.50	0.48	0.46	0.41	0.37	0.36	0.36	0.36	0.36
Jiangxi	0.24	0.23	0.21	0.21	0.20	0.18	0.17	0.16	0.16	0.15	0.15	0.15
Liaoning	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Inner Mongolia	0.36	0.34	0.34	0.33	0.30	0.27	0.24	0.22	0.21	0.20	0.22	0.22
Ningxia	0.41	0.40	0.37	0.40	0.35	0.29	0.25	0.25	0.25	0.24	0.25	0.23
Qinghai	0.26	0.22	0.23	0.22	0.22	0.22	0.20	0.18	0.17	0.16	0.16	0.15
Shandong	0.54	0.53	0.46	0.45	0.43	0.41	0.38	0.35	0.34	0.32	0.32	0.32
Shanxi	0.24	0.25	0.26	0.24	0.23	0.22	0.23	0.24	0.22	0.22	0.27	0.23
Shaanxi	0.35	0.35	0.34	0.32	0.30	0.28	0.27	0.28	0.27	0.25	0.25	0.24
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Sichuan	0.16	0.16	0.16	0.16	0.15	0.14	0.14	0.16	0.16	0.14	0.20	0.20
Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Xinjiang	0.30	0.29	0.28	0.27	0.26	0.24	0.23	0.21	0.20	0.19	0.19	0.19
Yunnan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zhejiang	0.74	0.69	0.66	0.62	0.61	0.56	0.51	0.51	0.51	0.48	0.47	0.47

Data Source: The data is obtained by calculating in the table and given in this paper.

regard as a group of standards by which the value level of other provinces will be judged. Through further exhaustive analysis, it has revealed that even if these cities with more developed economics depend more on the resource and environment, they invest more on pollution regulation. Fujian Province was efficient between 1998 and 2006.Although the values keep a higher level in the subsequent three years, it was not efficient. Apart from these six provinces above including Zhejiang, Jiangsu and Shandong, three provinces whose values are more than 0.5 in some particular years, the other 19 provinces all hold the value less than 0.5, which means that the environmental efficiency of most provinces in China is at a low level. The group of provinces with the lowest values contains Guizhou, Jiangxi, Qinghai and Sichuan, of which the average value is less than 0.2. What is worse, these provinces get farther and farther from the frontier. In reference with Beijing, Tianjin, Shanghai, Liaoning and Yunnan, if the same input and output is given, Guizhou, Jiangxi, Qinghai and Sichuan might reduce by around 80% in their pollutant emission, which indicates that there exists significant differences in environmental efficiency among each province and these provinces with lower values have more potency. The provinces with obviously declining values include Zhejiang, Shandong, Jiangsu and Guangdong even though these provinces can be counted as economically developed regions. In consideration of their high energy consumption and high pollution, their values have a declining trend.

In Table 2, the largest one of these values is 1 which satisfies the condition that the dependent value is a fragment one. Thus, to set the efficiency as the dependent variable and influencing factors as the explanatory variables, and then use the Tobit panel regression model to compute the influence degree of the economic development level, open degre and affect the environment protection and region factors, etc. The concrete expression is provided:

$$EE_{it} = \alpha_0 + \alpha_1 LN(GP) + \alpha_2 ISG + \alpha_3 FG + \alpha_4 TG + \alpha_5 CG + \alpha_6 EA + \alpha_7 LN(PD) + \varepsilon_{it} \quad (2)$$

t represents the year; i means the province; EE_{it} refers to the environmental efficiency; α_i (i=1,2,...7) is the unknown parameters; *GP*, *ISG*, *FG*, *TG*, *CG*, *EA* and *PD* express the environmental efficiency of the ith province in the tth year; ε_{it} is the stochastic disturbance item, obeying independent and distributed normal model. The correlation analysis is testing each of the influencing factors, and the result indicates multicollinearity.

5. Empirical analyses

5.1. Descriptive statistics of indexes

Before the regression analysis of the Tobit model, descriptive statistical method is applied to the environmental efficiency of provinces and their influencing factors. The result is below in Table 3.

5.2. Parameter estimation and statistical test

The SBM model to the estimation of the environmental efficiency values in each province is based on 28 provinces in China, a Tobit regression analysis is made on the environmental efficiency, and is defined as the dependent variable when the GDP per capita, industrial structure, dependence on foreign capital and trade, strength of environmental protection, awareness and population density are designated as the explanatory variables. The result is listed in Table 4.

In order to verify the reliability of the analysis result, the paper applies the proportion of each province's GDP and China's GDP to depict the economic development level. In that way, the robust test is made on the result of the Tobit regression. The result is below in Table 5.

The partial regression coefficient, standard error, *Z*-value, *p*-value, the statistics of log likelihood statistics and chi-square value of each explanatory variable can be obtained from Table 4. Considerable values of log likelihood statistics indicate that the

Table 3
Environmental efficiency of each province and their influencing factors.

Variable	Mean	Standard deviation	Maximum	Minimum	Observed number
EE	0.45	0.30	1.00	0.11	336
Ln (*GP*)[a]	9.39	0.71	11.28	7.77	336
ISG	0.39	0.07	0.56	0.19	336
FG	0.03	0.03	0.15	0.00	336
TG	0.32	0.42	1.72	0.03	336
CG	0.00	0.00	0.01	0.00	336
EA	0.01	0.01	0.07	0.00	336
Ln (*PD*)[b]	5.35	1.27	7.70	1.94	336

Note:
[a] the natural logarithm of GP (the proportion of the local GDP);
[b] the natural logarithm of PD (the proportion of the total population to the regional area from 1998 to 2009).

Table 4
Result of Tobit regression.

Variable	Estimating coefficient	Standard error	*Z*-value	*p*-value
Ln (*GP*)[a]	0.480	0.015	2.990	0.003
ISG	−1.034	0.241	−4.290	0.000
FG	2.081	0.834	7.290	0.000
TG	0.107	0.059	1.790	0.074
CG	4.021	0.728	1.640	0.103
EA	1.362	2.092	3.520	0.000
Ln (*PD*)[b]	0.017	0.015	2.090	0.008
Constant	0.094	0.109	0.860	0.390
Log likelihood ratio	−81.649			
LR chi2 (7)	235.910			
Pseudo R2	0.680			

Note:
[a] the natural logarithm of GP (the proportion of the GDP to the local population);
[b] the natural logarithm of PD (the proportion of the total population to the regional area by the end of the year).

Table 5
Result of robust test.

Variable	Estimating coefficient	Standard error	*Z*-value	*p*-value
GZ	1.040	0.216	3.820	0.000
ISG	−0.933	0.286	−4.450	0.002
FG	2.050	0.842	6.370	0.000
TG	0.094	0.054	1.750	0.081
CG	3.080	0.525	1.450	0.141
EA	2.110	2.019	3.550	0.000
Ln (*PD*)	0.019	0.016	2.130	0.007
Constant	0.051	0.506	1.180	0.145
Log likelihood statistics	−87.022			
LR chi2 (7)	248.170			
Pseudo R2	0.704			

model as a whole is highly significant, in other words, all explanatory variables have strong explanatory powers on the environmental efficiency. In addition, the corresponding p-value 0 denotes that the model carries no heteroscedasticity. These explanatory variables except the constants CG can pass the significance test at 10% level with noteworthy differences. Except the industrial structure, the average GDP in China, its dependence on foreign capital, trade, environmental protection strength and environmental awareness, as well as population density, all have positive impacts on the ecological efficiency. On condition that other factors remain unchanged, if the average GDP is increased on average by 1%, then x the value of environmental efficiency increases by an average of 0.0048. Similarly, those other biased regression coefficients can also be given economic explanations: a 1% increase in the proportion of the actual FDI to GDP will lead to averagely a 2.081 unit increases in the value of environmental efficiency. In conclusion shows that a 1% increase in the proportion of the total amount of external trade to GDP will cause a 0.107 unit increases on average in the value of environmental efficiency, and a 1% increase in the proportion of investment in industrial pollution regulation to the GDP will bring about a 4.021 unit increases in the value of environmental efficiency on average. Similarly, a 1% increase in the proportion of the population with an education level will cause averagely a 1.362 unit increases in the value of environmental efficiency. It accounts that a 1% increase in the proportion of the total population in the regional area by the end of the year will result in a 0.00017 unit increases on average in the value of environmental efficiency. Besides, the industrial structure has significant and negative influences on the environmental efficiency. On condition that other factors remain unchanged, if the proportion of the industrial production value of the local GDP is increased on average by 1%, nevertheless the value of environmental efficiency will decrease by an average of 1.034.

The regression results show that the average GDP has a larger influence on the environmental efficiency. Therefore, we can select the proportion of the provincial GDP aggregate GDP in China to mirror the economic development level, and then make a robust test on the entire model. It is known from the test result of Table 5 that the entire model passes the test and there are few significant changes in the influences of all these explanatory variables on the environmental efficiency, which indicates that the Tobit regression result above is brilliant.

5.3. Analysis of regression

Depending on the Tobit regression result above, we explore the impacts on the environmental efficiency in China, respectively.

By the factors with positive impacts on the environmental efficiency, average GDP in China, dependence on foreign capital and trade, environmental protection strength, environmental awareness and population density of all play notably positive roles in promoting at a high level, and pass the significance test. On condition that other factors remain unchanged, the proportion of the actual FDI to the GDP, the proportion of the total amount of foreign trade to the local GDP, the proportion of the population with a high educated, the resident population per square kilometer each increased on average by 1%, then the value of environmental efficiency will, respectively increase by an average of 0.0048, 2.081, 0.107, 1.362 and 0.00017.

Average GDP is comparatively suitable for the economic strength and competitive power of one country or region because only the economic development can really help to protect the environment. Moreover, the continuous improvement of China's economic level and enlargement of economic scale will be accompanied by the accumulative effect. With the increase in income level, the populace's requirement on the environmental quality will crawl up, which might boost up the environmental efficiency.

From Table 4, we can see that the degree of opening-up has an obvious positive impact on the environmental efficiency, and among all these factors actually utilized external direct investment has the most noticeable influence. China has those problems such as deficiency of management experience, relatively backward technology and shortage of capital, the direct overseas investment. Through the personnel training, liquidity effect, demonstration effect and industry forward and backward relationship effect, China has a new level. Although the external investment damages the improvement of the environmental quality in the developing countries, maintaining and enhancing their statuses in the international market will improve their environmental protection standards in their production process in the pursuit of the maximum benefits. Those advanced environmental management methods and the technology of pollution prevention and regulation will also be spread to promote these country's environmental quality to some extent. The import and export trade, through the application of capital, advanced technology and facilities in developed countries and the diffusion of international technology plays a pretty vital role in the global division of labor to efficiently deploy the resources, throughout the entire world and enhance the labor productivity. Comparatively, it is easy to find out that the degree of opening-up has less powerful influence than dependence on foreign capital, which denotes that the pulling effect of the import and export trade is weaker than that of the foreign direct investment.

The positive correlation coefficient between the public environmental awareness and environmental efficiency is as much as 1.362, meaning that the public environmental awareness is vital to the improvement of environmental efficiency. Every human act can affect the environment, so we need to possess and strengthen the environmental awareness, and two aspects need to be noticed. The strength of public environmental awareness cannot only reflect the civic quality, but also act as the benchmark to measure the social civilization level of one country, thus strengthening the public environmental awareness is the essence of the environmental protection. Although it is likely not a wise decision in this paper to use the education level to reflect the public environmental awareness, some studies shows clearly that it is necessary to transform the increasing public environmental awareness to the principal motive power of the augmentation of social management capacity.

The population density plays a positive role in promoting the environmental efficiency. Whether the population is beneficial or not, the proper population density that is closely related to the region can ensure the economic development and prosperity. Generally speaking, the population density in the eastern coastal regions is comparatively higher than in the western regions of China. As eastern coastal regions are highly developed and western regions are opposite, the population density with the economic developmental level can be drawn. The increase in population density can indirectly promote the environmental efficiency in some degree.

Environmental protection strength of the environmental efficiency is positive but not significant impact. The proportion of investment on industrial pollution regulation to the GDP is positively correlated with the environmental efficiency, but fails in passing the significance test at 10% level, despite the pollution regulation that can promote the environmental efficiency, and the effect is inconspicuous. This point reminds us that, improving the environmental efficiency needs us to save energy and reduce pollutant emission in the first place rather than harness the pollution in the end. Industrial pollution regulation referred in this paper involves self-financing of enterprises as well as government

subsidies. The investment of government can benefit from the pollution regulation. The pollution might be aggravated in case that those apply the invested capital to the increase of processing and manufacturing.

The industrial structure on the environmental efficiency is negative and significant. Herein this paper selects industrial proportion to evaluate the industrial structure's impact on the environmental efficiency and finds out that this impact is negative and succeeds in passing the significance test at the 1% level. On condition that other factors remain unchanged, if the proportion of the industrial production value of the local GDP is increased on average by 1%, then the value of environmental efficiency decreases by an average of 1.034. In other words, it indicates that the industry in China is still developing in the traditional extensive economic growth mode at the price of large energy consumption and serious environmental pollution. Its consumption mainly shows two different aspects. One is that predatory resources exploitation can seriously destroy the resources base. The other is that the waste of resources is severe and the utilization efficiency of resources is rather low.

6. Conclusions

To sum up, the paper selects input indexes, and adopts output indexes and the SBM model evaluates the environmental efficiency of 28 provinces in China from 1998 to 2009. On the basis of theoretical analysis and a literature review, this paper selects some effective influencing factors of environmental efficiency and makes the regression analysis on the environmental efficiency and its influencing factors to succeed in the empirical test of various factors. The main conclusions are as follows.

First, the environmental efficiencies of many provinces are at a minimal level with an essentially descending trend. There exists a significant difference in environmental efficiency between each province. Beijing, Tianjin, Shanghai, Liaoning and Yunnan are efficient with the highest value of 1. Compared with the cities of highest value, if the same inputs and outputs are given, Guizhou, Jiangxi, Qinghai and Sichuan might decrease by around 80% on pollutant emission to be efficient. Second, GDP of the average per capita (the average GDP), dependence on external capital and trade, environmental awareness and population density have obviously decisive impacts on environmental efficiency. Environmental protection strength has a positive but not remarkable impact on environmental efficiency. The proportion of the secondary industry to the GDP poses a significantly negative impact on environmental efficiency.

To improve the environmental efficiency, China needs to accomplish the following aspects. First, change the mode of economic growth. With the economic development, the environment should be paid more attention. Second, some big modern cities, like Beijing, Tianjin, Shanghai, Liaoning and Yunnan, should develop themselves to build a resource-conserving and environment-friendly society. Third, facilitate the equalization of the compulsory and secondary education, and improve the general education level to strengthen the populace's environmental awareness. At last, the government should concentrate more on the absorption and utilization, and enhance the dependence of the external capital in moderation. Moreover, it is necessary to increase the competitiveness of domestic products in the international market, and optimize the industrial structure through improving the tertiary industry.

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